# Ceramic Cracks Segmentation with Deep Learning

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## Abstract

Cracks are pathologies whose appearance in ceramic tiles can cause various types of scratches due to the coating system losing water tightness and impermeability functions. Besides, the detachment of a ceramic plate, exposing the building structure, can still reach people who move around the building. Manual inspection is the most common method for this problem. However, it depends on the knowledge and experience of those who perform the analysis and demands a long time to map the entire area and high cost. These inspections require special equipment when they are at high altitudes, and the integrity of the inspector is at risk. Thus, there exists a need for automated optical inspection to find faults in ceramic tiles. This work focuses on the segmentation of cracks in ceramic images using deep learning to segment these defects. We propose an architecture for segmenting cracks in facades with Deep Learning that includes a pre-processing step. We also propose the Ceramic Crack Database, a set of images to segment defects in ceramic tiles. The results show that the proposed architecture for ceramic crack segmentation achieves promising performance.

## 1. Introduction

In civil construction, buildings must be able to withstand the action of degradation agents for a predetermined or predicted time (Possan & Demoliner, 2013). The building's facades include the cladding system that serves to protect the building from external degradation agents, in addition to providing functional and aesthetic comfort to its users (Costa e Silva & Franco, 2001). Pathological manifestations are common at these points, and they occur more frequently in ceramic materials, which are used on a large scale in buildings. Besides, these manifestations arise in other types of materials, such as mortar and stone. They can be related to several factors such as excessive load, humidity variation, thermal variation, biological agents, material incompatibility, and atmospheric agents (Galletto & Andrello, 2013). These manifestations compromise the essential function of protection, which aims to protect the coated surfaces against the agents that cause deterioration that can present themselves in different ways. Thus, the consequences can range from aesthetic problems or performance of coating to risks of accidents with people, substantially aggravated by the height of the buildings (Luz, 2004).

The main types of pathological manifestations associated with ceramic facade coverings are cracks, efflorescence, detachment, and those resulting from biological processes. Among these, the fissure is the most found in literature since it compromises the building safety, puts at risk the people that travel around it, and presents a more critical aesthetic aspect (Galletto & Andrello, 2013; Horsth et al., 2018; de Freitas et al., 2013; Toledo, 2007). In Brazil, the inspection of this type of pathological manifestation on facades, for the most part, is carried out by the traditional method, which includes the industrial climber who can perform visual verification and photographic record of the main points to be analyzed.

There are currently many image processing techniques (IPTs) applied in civil engineering for images collected from inspections. These techniques emerged to detect cracks in the civil infrastructure, partially reducing the work done by human beings, and used several image processing techniques to extract characteristics of cracks in the surfaces of the images (Cha et al., 2017). However, many structure analyses and inspections are carried out manually, and this requires a lot of knowledge, experience, and time from those who will perform this activity.

Automatic crack detection is essential in places that are difficult to access due to height or scale, avoid exposing people to dangerous situations, and speed up the inspection process (Yang et al., 2018).

Therefore, to create an automatic solution for the detection

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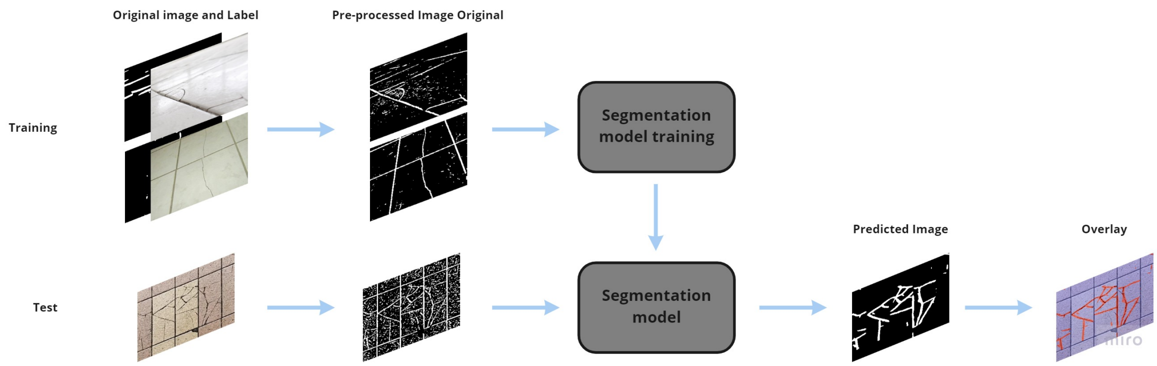


*Figure 1.* Architecture for crack segmentation.

of cracks in ceramics, in this work, we focus on a methodology that includes pre-processing and deep learning to solve the problem of ceramic crack detection. We created a database to implement the segmentation models that contain images from defective ceramic tiles and the ground truth of the crack to each image.

## 2. Crack Segmentation of Ceramic Surface

This work presents an architecture for segmenting cracks in facades with Deep Learning that includes a pre-processing step and a deep neural network for segmentation proposal followed by a threshold operation, as shown in Figure 1. The output is a binary image that brings white lines where the cracks were located, and, through overlapping images, it is possible to highlight the cracks in the original image. In this approach, pre-processing is done in the database before using the segmentation model. The pre-processed image with its label is adopted as input to perform the model's training. After training, only the original image is needed to run this network.

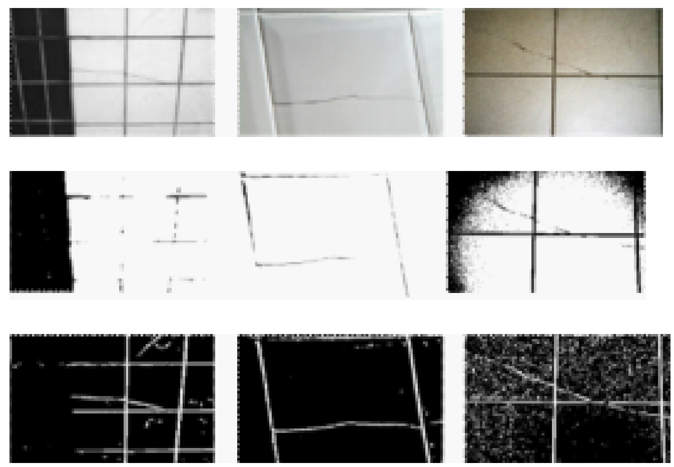

*Figure 2.* Example of a pre-procesing: (up) Original image, (middle) Simple binarization, and (down) performed pre-processing on the original image.

### 2.1. Data Pre-processing

The techniques used for image processing at the input are: Histogram equalization; Gaussian filter (with kernel 3x3); Light and contrast adjust; Inversion; Erode and dilate functions (with kernel 5x5); Finally, Otsu thresholding.

As seen in Figure 2, the pre-processing result highlights the area of interest, becoming much more in evidence, thus facilitating the neural network's performance in the extraction of characteristics.

### 2.2. Segmentation Model

In the segmentation model, the U network was used, a neural network proposed by Ronneberger et al.(Ronneberger et al., 2015), which stand out in the segmentation problems due to the better performance, even with few images for training.

The peculiar name of U-Net is due to the ”U” shape of its architecture The network input is the image that needs to be segmented. The output is the image label, a label that represents the model's expected output.

The network has a typical convolutional network architecture; however, it has two complementary paths, the contracting path (left side) and the expansive path (right side). The contracting path handles executing controls to extract characteristics from the image. This process reduces the dimensionality and increases the filters applied to extract features, generating a map for each level. On the other hand, the expansive path handles reducing the filters and increasing the dimensionality. A concatenation process is performed with the correspondingly cropped feature map from the contracting path to reach the segmented image's formation.

# 3. Methodology

We propose a ceramic crack database with 167 ceramic crack images. The images were collected by the University of Pernambuco from the civil engineering department. The database consists of images of a fixed resolution of $256 \times 256$ in RGB format without any previous pre-processing. Each element is labeled with a binary image of segmented cracks, where the white pixels represent the pathology and the black pixels represent the background. The database presents diversity in different sizes, angles, illumination, distance, or even materials and textures. Moreover, the database has images of building facades with ceramics with cracks of different shapes and deepness.

The database was manually labeled and it will be available for public use in future works related to the ceramic crack segmentation problem at the link https://github.com/gerivansantos/ceramic-cracks-dataset.

## 3.1. Experimental Setup

This paper sets a benchmark over the proposed database, utilizing state-of-the-art models. The data distribution is as follows: $70\%$ of the data is randomly allocated towards training and $30\%$ towards testing in the several experiments performed, which were used as comparative parameters for the database. The models selected for this purpose were U-Net (Ronneberger et al., 2015), and LinkNet (Chaurasia & Culurciello, 2017). The criteria for its selection are the relevance in image segmentation literature and good accuracy in solving the proposed problem.

We use the different architectures for model's backbone, like resnet34 (He et al., 2016), resnet50 (He et al., 2016) and vgg16 (Simonyan & Zisserman, 2014). The initialization of the weights can be carried out randomly, or using the weights of the pre-trained neural network with the ImageNet database (Deng et al., 2009).

Input images have $224 \times 224$ pixels to U-Net and LinkNet models. We apply the Adam algorithm for optimization, a stochastic gradient descent method based on the adaptive estimation of first-order and second-order moments (Kingma & Ba, 2014). In our experiments, we set the hyperparameters to the Adam algorithm with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-07}$, with learning rate of $\alpha = 0.001$. A total of 20 experiments are performed 30 times to ensure that the results were statistically significant, and from them were extracted the metrics used to compare the results. Additionally, since fine-tuning presents good results in deep learning applications, we analyzed its efficiency in this work approach.

# 4. Results and discussions

The models are selected according to their success in the segmentation of images, as previously presented. After that, 20 fine-tuning experiments are performed, altering the models' backbone and the weight initialization. Table 1 outlines each model's three best results, utilizing the IoU metric.

In terms of average IoU, our U-Net model approach overcame the IoU value from the other models. We obtain an index of 86.5% in our approach, and in the U-Net and LinkNet models, the value is around $68\%$. The obtained average precision in our approach in the U-Net model reaches a value of $99.9\%$. The U-Net and LinkNet models demonstrate that the resnet50 and resnet34 models, when initialized with the ImageNet weights, present an average precision of $72.7\%$. Regarding the average recall, to U-Net with resnet50 backbone, without weight initialization, and LinkNet with restnet34, initialized with the ImageNet weights, obtained percentages equal to $94.6\%$. This value overcomes the average recall of our approach, with a value of $78.7\%$. Our approach shows a high value of accuracy and a low recall. However, most of our predicted labels are correct.

Regarding the confusion matrix generated, our approach correctly classified $99\%$ of the pixels that belong to the crack. However, $27\%$ of the pixels that are not from the crack are classified as part of it. Using the U-Net model, resnet50 with the random initialization, $95\%$ of the pixels are correctly classified as cracks.

A qualitative analysis shows that our approach obtained a thicker segmentation compared to the other predictions, overestimating the region where the crack is, but fine segmentation can lose the representation of cracks, which in this case is much more harmful than overestimating, since that we need to identify the area of trica for future analysis.

# 5. Conclusion

In this work, we analyze deep learning models' capabilities in the segmentation of cracks in ceramics tiles. We propose a pre-processing methodology to improve the performance of models to ceramic crack segmentation. Besides, we present the Ceramic Cracks database, a set of images with ceramic tiles with cracks destined for crack segmentation. Our results show that it is possible to identify cracks in ceramic images. The crack is identified with a high precision value in the model using a pre-processing methodology. Nevertheless, the crack, in some scenarios, is overestimated by the prediction. The U-Net and LinkNet models achieve good results, using the resnet50 and resnet34 as backbones, respectively, and the weights of a pre-trained network with ImageNet to initialize. By increasing the number of epochs during training, the models manage to segment cracks even

*Table 1.* Result of the metrics for the U-Net and LinkNet models, and the different network architectures. The weights of a pre-trained network with ImageNet are used to initialize each of the models.

| Metrics | Models | | | | | | |
|---|---|---|---|---|---|---|---|
| | U-Net | | | | LinkNet | | |
| | Approach† | resnet50† | resnet50 | resnet34 | resnet34 | resnet34† | vgg16 |
| IoU | 0.865 | 0.685 | 0.681 | 0.675 | 0.697 | 0.684 | 0.672 |
| Precision | 0.999 | 0.713 | 0.727 | 0.720 | 0.727 | 0.711 | 0.704 |
| Recall | 0, 787 | 0.946 | 0.933 | 0.929 | 0.946 | 0.922 | 0.897 |
| Kappa | 0.724 | 0.805 | 0.808 | 0.803 | 0.814 | 0.794 | 0.775 |
| Specificity | 0.999 | 0.988 | 0.988 | 0.988 | 0.988 | 0.987 | 0.988 |

For these models, weights were randomly initialized.

when they are in the tiles' grout.

This paper then contributes to a new segmentation problem and a new database for crack segmentation in ceramic tiles. We also intend to study the computational cost of the proposed solution and other solutions in the literature, we expect to implement this work in drones for optical facade inspection, which allows a more efficient inspection at a low cost.

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